Technology and Society

Computer Science

Bachelor's thesis

15 credits, ground level

Development of algorithm for a mobile-based estimation of heart rate

Utveckling av algoritm för en mobilbaserad pulsuppskattning

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Exam: Bachelor of Science in Engineering

Area: Computer Science

Program: Data & Mobil IT

Date for examination: 2021-05-25

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Acknowledgments

We would like to express our gratitude towards our supervisors Carl Magnus Olsson and Dario Salvi for their assistance during every interactive process concerning developing and writing in this thesis. Their expertise on the subject has led to many good discussions and has allowed us to expand the way we approach challenges. We would also acknowledge John Lindahl for providing us with a mobile device Finally, we want to thank our examinator Reza Malekian for good questions and notes on improvement during our thesis.

I, Dennis, would like to thank Johan for being an excellent partner and friend. I hope I never have to do this again but if I do, I wish I get to do it with you. I also want to extend a great thank you to Wilma for helping me with this thesis and volunteering as a participant for our work.

I, Johan, would also like to thank Dennis for being an excellent partner during the development of our algorithm and the writing of this thesis. I would also like to thank both Dennis and Wilma for being our test subjects and performing the QCST for this thesis.

Abstract

To perform a physical performance test is a good way to keep track of one's health and can be beneficial to find evidence of deviations in the body. This thesis focuses on the development of a mobile-based heart rate algorithm that can be used with the Queens College Step Test, on the behalf of Mobistudy. Mobistudy wants to include such a test in their mobile application which aims to become a tool for researchers to use to gather data. The algorithm uses the mobile device's camera to collect data from the user's finger and uses that data to calculate the heart rate. The algorithm was first tested with data collected during the development and the results has an average error of less than 5% and a standard deviation of less than 3%. Two participants between the age of 20-25 performed three sets each of the Queens College Step Test and the results showed that the algorithm was accurate in its estimation of the heart rate after the test.

Sammanfattning

Genom att utföra ett test av ens fysiska prestanda kan man utvärdera ens hälsostatus och upptäcka indikationer på avvikelser i kroppen. Syftet med detta arbete är att utveckla en mobilbaserad algoritm som kan beräkna och uppskatta ens puls när man utför the Queens College Step Test på begäran av Mobistudy. Mobistudy vill inkludera detta test i deras mobilapplikation som fokuserar på att kunna användas som ett verktyg inom forskning för att samla in data. Algoritmen använder sig av mobilens kamera för att samla in data från användarens finger och använder den insamlade data för att beräkna pulsen. Algoritmen testades först gentemot data som samlades in vid utvecklingsstadiet och resultatet visade på att genomsnittliga felet var under 5% samt att standardavvikelsen var under 3%. Två deltagare mellan åldern 20 och 25 utförde tre tester var utav the Queens College Step Test och resultatet visade att algoritmen var tillräckligt noggrann i sin uppskattning av pulsen efter ett utfört test.

Glossary

QCST The Queens College Step Test

PPG Photoplethysmogram

BPM Beats per minute

FPS Frame per second

PCP Primary care provider

OS Operating systems

FFT Fast Fourier Transform

ECG electrocardiography

ICA independent component analysis

DSRM design science research methodology

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1 Introduction

Having a personal awareness and the knowledge about one's health is important. Keeping track of one's health can be beneficial as it helps to indicate deviations in the body. This can be done by tracking steps during the day, check the pulse in a state of rest, or get a physical examination by a PCP. The information gathered from tracking steps, heart rate or both is on its own not enough to give a personal evaluation on an individual's state of health. The individual's age, gender, weight, and length are some of the information that needs to be considered during the evaluation. The same conditions also applies when the PCP is preforming a physical examination on a patient. A physical examination, more commonly known as a wellness check, is done in a hospital or in a clinic, and is performed by medical staff.

There are several different types of physical examinations that can be performed to examine the patient's physical health such as the QCST, VO2max-test, and a lactate certificate-test [1] [2] [3]. These tests require different levels of athleticism, resources, and conditions to be performed, this also mean that the test will contribute with different levels of health states for the patient that performs them. For example, VO_2 max-test require a treadmill or a bike to perform the test and a training mask that is connected to a calculator to calculate the oxygen levels during this highly intensive test [3], while the QCST only requires a heart rate monitor and a stable object that the patient can step up to. Both tests are used to monitor the cardiovascular system at some level but the QCST being the less resource and athletically demanding one [4]. The PCP use these different tests to make a physical examination to determine if a patient is showing any signs or symptoms of impaired health, which in turn allows the PCP to treat the symptoms before they become severe.

Several parts of the different examination use technology as aid in cases where exactitude is key or to simplify and speed up the process [5]. Manual calculations of heart rate are one example where advanced devices are being used to mitigate false readings and unprecise results, which in turn relieves some of the high amount of pressure on the medical staff [6]. To further unburden the hospitals and their staff, applications on the subject of mobile health are being developed. The possibilities to move parts of the examination to a mobile device or a smartphone application would mean that data needed for the exam could be gathered by the patients themselves without the need of being in a hospital or the help of a PCP [7].

Mobile health applications and mobile phones can also be used as a tool in healthcare, but also within research, for its capability to collect data without the need for participants to visit a clinic or the researchers. Iribarren et. al. [8] summarized the evidence of rigorously and evaluated health related applications on health outcome. By exploring the effects of features that was present in studies that reported a statistically significant difference in health outcome.

1.1 Problem Domain

Performing clinical research or studies where large amounts of information is needed can be hard to conduct. E.J. Emanuel et al. [9] report on the cost of performing clinical research. They surveyed and collected data from clinical sites on the number of hours associated with activities that are necessary when conducting a clinical research. 20 patients were enlisted in a 12-month randomized placebo-controlled trial for a new chemotherapeutic agent and the hours it took was the base for the research. The result showed that research involving 20 subjects with 17 office visits took on average 4,012 hours for a government-sponsored trial and nearly as much for a pharmaceutical industry-sponsored trial. The average cost per enrolled subject in an industry-sponsored trial is slightly more than $6,000 (ranging between $2,098 and $19,285) [9].

A clinical trial can be affected by loss of data in non-returning participants which in turn can lead to a significant decrease in reliability and interpretability. In [10] T.R Fleming addresses the concerns of missing data and its effect on clinical trials. In his research he studied how many participants that would drop out during a two-year period. The result showed that more than 40% had dropped out since the beginning of the study [10], further showing issues within the clinical research. This shows that it is not only expensive to conduct a clinical research, the research itself can be deemed unreliable for lack of data.

1.2 Problem Discussion

The increased popularity of smartphones with its equipment and its wide array of sensors has the capability to collect high amount of relevant data, for example steps, heart rate, sleep, or other conditions. In the domain of healthcare, research, and application development these types of data can be of high value considering the large amount of data that can be extracted from mobile phones with relative ease. The smartphone has been shown as a promising platform to provide solutions to widespread care and better patient health. For instance, a patient with the usage of a smartphone can produce raw data to an application that is used for healthcare or research. Also considering the high number of patients that are going to a doctor at a hospital or a clinic, instead the doctor can use the data from the smartphone to determine their health in certain aspects [11]. From a research point of view, one can gather necessary data from multiple volunteers that are willing to share their information without the need of ever meting them [12].

An example of how mobile phones can be used in research is Mobistudy, an open-source framework and a mobile phone application which aims to simplify for clinical research to include digital technology. Mobistudy provides researchers with a way to conduct clinical studies online by defining inclusion criteria and letting them decide what data they are in need of. Users can be invited and asked to contribute by generating data to be used in research, either via forms created by the researcher or by performing a physical health test with their phone [12]. Not every physical health test is viable to transfer and perform with a mobile device since some require specific equipment e.g., the VO2max-test presented in section 1. The QCST, however, requires far less resources to perform, and an integration of that physical test into a mobile device is therefore feasible and a suitable test for Mobistudy to provide. Given that heart rate is the main parameter used to assess patients in a QCST, it is important that such variable is measured reliably. Users of the Mobistudy app can count pulsations, but this is usually unreliable and not always feasible, therefore an automatic way for measuring the heart rate should be provided by the app itself.

1.3 Research Questions

The aim for this thesis is to develop an algorithm for the calculation of the heart rate that can be used when participants perform the QCST in the Mobistudy's app. Two research questions are posed:

- RQ1: How can heart rate be computed by a mobile phone during a step test?
- RQ2: How can the heart rate accuracy of the algorithm be determined?

1.4 Limitations

This thesis is conducted on behalf of Mobistudy, and the solution is expected to be used in their application. Therefore, this thesis is limited to the same framework and requirements that comes from their application e.g., the use of Apache Cordova. The focus will be on two suitable approaches that has been tested in other use cases for calculation of heart rate together with PPG.

2 Theory and Technique

This section gives an overview of the theoretical aspect of this thesis. The information provided will give the reader an insight into general aspects for different parts within this thesis.

2.1 Mobistudy

Mobistudy is an open-source platform for mobile phone-based health research. The aim of Mobistudy is to make it more convenient and easier for researchers to get access to data in this field. Mobistudy connects the researchers to participants that uses the application. Researchers publishes their study within the application and participants can then decide if they want to contribute to the study that has been published. Mobistudy is meant to work for everybody that has access to a smartphone. Participants participate by answering questions, performing simple exercises and by submitting the data that is gathered by other health apps, such as Healthkit and Google Fit [12] [13]. Data that can be submitted can be the number of steps that has been detected or hours of sleep registered.

2.2 The Queens College Step Test

The Queens College Step Test is a step test procedure, used to determine aerobic fitness and to measure one's cardiorespiratory. The test involves minimal equipment and costs, as mentioned in the introduction, and only needs a 41.3 cm step up object and a heart rate monitor to perform. The test is executed so that the athlete steps up and down on the platform at a rate of 22 steps per minute for female and 24 steps per minute for male for a total duration of three minutes. The athletes need to step using a four-step cadence which is 'up-up-down-down'. After three minutes, the athlete counts the number of pulses for 15 seconds and then multiplies it by four to get the BPM. The BPM is then compared to a scale to determine the result [4] [14].

2.3 Photoplethysmogram

PPG is a technique used to measure changes in volume within organs or body parts. The PPG method is used in the medical field to detect blood volume changes in the microvascular bed of tissues. PPG is for example used in a medical device called pulse oximeter. The device is used to monitor volume changes of blood when a finger is put between its staples and determines the heart rate. The technology of PPG is based on two different modes: transmissive absorption or reflection [15].

The different modes provide two different ways of measuring changes in the blood. In transmissive absorption a light source is placed on the opposing direction from where the light is measured. In the reflection mode the light source and where the light is captured are on the same side.

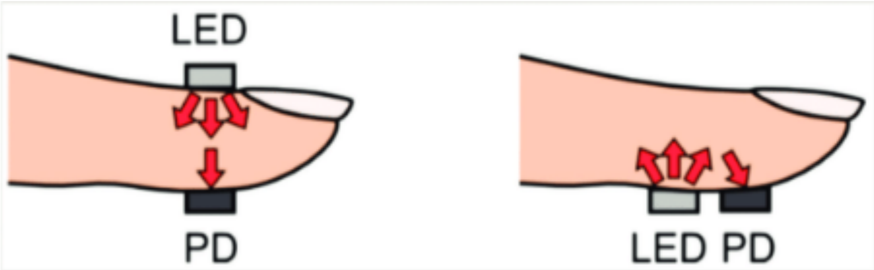

Figure 1- Showing a LED lighting up and a photodetector (PD) that takes the picture [16].

In both modes, the light is travelling through the biological tissue and the photodetector can measure the blood volumes changes in the tissue. When the light hits the blood vessels it creates diffused reflection, which is the reflection that the photodetector captures [17] [18].

2.4 Hybrid applications

Apache Cordova is a mobile application development framework that allows developers to create hybrid web applications. Cordova uses CSS3, HTML5 and JavaScript combined instead of relying on platform-specific APIs like Android, IOS or Windows phone. Cordova wraps up CSS3, HTML5 and JavaScript coding depending on the platform of the device. This results into a hybrid application, meaning it is not native to a mobile application or a Web-based one. Hybrid applications allows developers to program an application for multiple OSs instead of needing to develop one for each OS. This is because all layouts are done via Web views instead of the platform's native UI framework [19] [20].

3 Related Work

In this section related work will be highlighted and discussed based on their significance for this thesis.

3.1 Real time heart rate detection from PPG signal in noisy environment.

In 2016 S. Das et al. [21] published a paper on real time heart rate detection from a PPG signal in a noisy environment. In their development they used an Arduino Uno board and an 8-bit AVR core microcontroller. Their research was based on extracting the periodic PPG signal from a contaminated non-periodic noisy signal. After the extraction they used an algorithm based on the autocorrelation to calculate the BPM.

In their research they used ten volunteers in a sitting resting position to extract the PPG signal from their right index finger which enabled them to collect clean data without noise. To create noisy data, they asked the volunteers to move the finger gently, by doing so they extracted both noisy and clean data to validate the algorithm. Because their research is based on using patients at rest state, their range of the BPM calculation is based on a resting state, which they have defined to be in between 50-120 BPM. The sample frequency they use within their hardware is 250Hz. They used the different sample value from the autocorrelation and the sample frequency to calculate the BPM.

This paper provides information about extracting heart rate from a PPG signal from the finger in resting state, and the usage of autocorrelation to calculate heart rate. This can be useful in our thesis to answer RQ1.

3.2 Using imaging Photoplethysmography (IPPG) signal for blood pressure estimation.

A recent study in 2020 R.J Goudarzi et al. [17] used PPG to estimate blood pressure. In their research they placed a camera one centimetre away from the patients' forehead to take pictures. They connected patients to a blood pressure device that is acting as a ground truth for validation. The camera is a Canon 80D and offers high-resolution images. A light source was placed above the camera and the patient. This would allow lights to enter the subcutaneous tissue of the patient, where the blood vessels are located, and reflect the light towards the camera. The capturing of the frames was limited to a box area on the forehead from which the pictures are taken. The picture consisted of three coloureds channels R, G and B, representing the colours red (R), green (G) and blue (B). In each 1000 extracted frame there is a vector of 3x1000, and for each row in the vector they represent the average intensity of the extracted colour channel.

This paper provides us with information about extracting coloured channels from a frame to calculate a value of RGB using the PPG. The RGB colour channel could be a solution for us to see the changes of colour in the frames, which then could be used to calculate the heartrate and answer RQ1.

3.3 Remote heart rhythm monitoring by Photoplethysmography-Based smartphone technology after cardiac surgery: prospective observational study.

In this study, made in 2021, M. Lambergits et al. [22] used PPG with a smartphone camera. Patients that were recovering from cardiac surgery were asked to register their heart rhythm three times a day using an administration-approved PPG-based application called FibriCheck. Patients were asked to register their rhythm for either 30 or 60 days after they got discarded home. The measurement of the heart rhythm was done by placing a finger on the camera of the smartphone for one minute while the flashlight is on. During this time, the applications sensors detected variations in the tissue related to the heart rhythm. Each measurement was then uploaded to a server and analysed by an algorithm and classified into 1 of 4 categories(normal, warning, urgent, insufficiency quality). This was sent to a doctor for an examination if the result did not come back normal.

The paper provides information about mobile health and PPG when it is implemented into an application. The application lets the patient do their own examination without the need of any medical staff taking their heart rate. This type of mobile health concept is within the area of this thesis therefore, this is valid information. The results of the PPG implementation with the using of a camera with the flashlight is a practical method that is useful for this thesis to answer RQ1.

3.4 Validation of heart rate extraction using video imaging on a build-in camera system of a smartphone.

In the paper [23] K. Sungjun et al. based their research on the validation of extracting the heart rate from images using the camera on a smartphone. In the research they set up an iPhone4 30 centimetre away from the subject’s face and using the front-facing camera to capture frames at 29.99 fps with a resolution of 640x480 pixels using an iPhone. The experiment was conducted using 10 subjects, 8 males and 2 females. To validate the camera, they used an ECG signal with electrodes attached to the subject’s body. The frames were divided into the three RGB colouring channels (red, green, and blue) and then normalized for each channel. The second step was applying ICA on the signal to extract a more accurate cardiac pulse signal. In the third step they analysed the power spectra of both the normalized signal and ICA using an FFT. The max power frequency of the FFT showed that the signal from the normalized was clearer than the ICA, which lead to a discard of ICA in their process.

The result confirms that a reliable heartbeat can be extracted from the camera in a smartphone. The method of dividing each frame and compute the different colour channels of the RGB and then normalize the signal, gave a better result than the same process but with the ICA. The result table in the paper showed an average of 1.08% error rate from the raw normalized signal of the smartphone, and a 1.47% error rate from ICA. Their result showed that applying the ICA process on the signal, did not improve the output of the signal enough.

4 Research Methodology

This section will cover the methods used to find and develop solutions to the research questions. A literature study was used to ascertain knowledge on how heart rate calculations can be extracted from raw data using an unmodified mobile phone as well as finding efficient and well documented architectural structures suitable for development of a concept to a prototype. The literature study was combined with DSRM published by Peffers et al. in [24]. DSRM is an iterative architectural structure that, in multiple steps, brings a clear approach from designing research questions to developing prototypes and evaluation [24] and was therefore chosen.

4.1 Literature study

A literature study was conducted as the primary source of information in regard to heart rate calculations in a mobile device as well as finding a suitable research methodology. Previous reports were studied to grasp how related work was created and their potential limitations. The purpose of the study was to establish knowledge to base this work upon.

The information was gathered from large databases such as ACM Digital Library and IEEEXplore Digital Library due to their large quantity of reviewed papers on technical subjects. Keywords used to specify the search to related areas were chosen to limit the number of articles. Mobile devices are continuously changing and therefore articles written before 2012 were not used in this study as our goal is to focus on the development in the more recent past. Exceptions however on sources used to provide general knowledge of the problem in section 1. Keywords used during the search was the following:

- Heart rate
- Photoplethysmogram
- Algorithm
- Mobile phone
- Health
- Mobile health
- QCST

For information regarding the software and other non-specified subjects, the information gathering was not limited to previously mentioned databases and broader searches on the internet was made.

4.2 Problem identification and motivation

Identification of the problem is the first step out of six in DSRM according to Peffers et al. in [24] and it is done by specifying the problem and from there derive research questions and later vindicate these questions via arguments.

Researchers can thereafter focus their attention on a narrower perspective of the problem and motivate their solution. The problem domain and derived research questions from this thesis have been presented in section 1 and are discussed and justified in a later stage of this thesis.

4.3 Define the objectives for a solution.

Peffers et al. describes in [24] that this step is for deduce and define the objectives for a solution in regard to the problem and knowledge of what is feasible and possible. The objectives should, rationally, be based on the posed research questions. For RQ1 to be answered an appropriate algorithm needs to be developed based on the knowledge gained from previous steps. To answer RQ2 the algorithm developed for RQ1 needs to be used and tested against a set of test cases and finally the full QCST.

4.4 Design and development

The third step is to create an artifact, broadly defined as methods, instantiations or models. One should in this step determine the artifact's wanted functionalities and thereafter develop the artifact. To move from the previous step to the design and development one requires knowledge of relevant theory that can be exploited as a solution. The design of this artifact can be divided into three parts, (1) collection of data from users, with an iPhone SE, (2) processing of the data that has been collected and (3) calculation of the heart rate. The first part was developed using JavaScript and the Apache Cordova framework. For developing part two and three MATLAB was used as it was deemed to fit our purpose and have useful tools implemented which was of use.

Each design developed for heart rate calculation was tested towards three signals with varying lengths and starting pulses. The first signal, signal A, tested how well the designs could estimate the BPM during a decrease in heart rate. Before the data acquisition of signal A, the user performed jumping jacks for 30 seconds to raise the heart rate above the resting pulse. After the 30 seconds the user stopped and entered a state of rest and began the data acquisition for a duration of one minute. It was used as it represented how the heart rate calculation in a QCST is performed during a state of rest after a physical activity. The second signal, signal B, had the user in a state of rest before and during the gathering of data. The duration of the signal was one minute. This signal was used to analyse how each design performed with a low varying heart rate. Signal C, the last signal, had the same prerequisites as signal B but a longer duration, five minutes. Signal C was needed as it tested how well each design performed during a longer period of time which indicated if it was possible to perform the heart rate estimations during a whole QCST, three minutes, or longer. The results are presented in section 5.

4.5 Demonstration

This step is for the researchers to demonstrate how the use of the artifacts solves one or more instances of the research questions. Activities such as experiments and tests where the artifacts are included can be used as further proof of its solution. The constructed artifact's capabilities in regard to the QCST was demonstrated as a final result. One male and one female performed the test three times each with a metronome during a QCST. In each test both the artifact and the ground truth were used so comparisons could be made in a later stage, and the tests were conducted as follows:

- 1 minute in a state of rest before performing the QCST.
- 3 minutes of performing a QCST following a metronome.
- 1 minute in a state of rest after the QCST.

The results of the demonstrations are presented in section 5 and for further reading on how to perform the QCST see section 2.2.

Ground truth

For a reliable ground truth, a *Polar pulse band H10 HR sensor* was used during the testing stages and was chosen for its high accuracy and compatibility [25]. The pulse band was paired with a heart rate logging application for IOS that provided downloadable files containing a heart rate value, with a timestamp, every second it was active and the time interval between two peaks, so called RR-interval [26].

4.6 Evaluation

The evaluation activity is used to measure the artifacts prowess to support the posed questions and observe previously gathered data. The signals generated from the tests during the demonstration stage were analysed and used for a comparison with the ground truth. The average error in precent, maximal and minimal error as well as the standard deviation between the three signals from a previous step, 4.4, and their counter part from our ground truth was calculated. These results were used to evaluate the artifact and presented in section 5. Final tests were conducted in regard to the QCST and thereafter evaluated, section 5.

4.7 Communication

The last step is to “communicate the problem and its importance, the artifact, its utility and novelty, the rigor of its design, and its effectiveness to researchers and other relevant audiences such as practicing professionals, when appropriate [24]”. This is accomplished by creating a discussion surrounding the results and regarding the artifacts functions. A conclusion and future work are presented in a later section of this thesis.

5 Result and analysis

This study has been conducted in three main phases, collection and processing of data from the camera, pre-processing of the signal, and the calculation of heart rate. All these phases were iterative in nature, as we worked to identify the problem in each phase as well as implement a solution for said problem and test our approaches. Below we present each of these phases ending each with the lessons learned from that phase. We return to these in the discussion to place our results in relation to the specific use case of QCST and our two research questions.

5.1 Collection and processing of camera data

We developed an application to be used for the collection of data from the back-facing camera of an iOS or Android mobile device using the Cordova framework. Its functionalities include (1) collect data from images taken by the camera with a given sampling frequency, (2) compute the average of the red, green and blue values of an image, as well as (3) write the computed values to a file together with a timestamp stored in a reachable location on the mobile device. To access what type of device is being used, iOS or Android, and storage locations for the device, different Cordova standard plugins were used. For accessing the camera, a plugin called Cordova-Canvas-Camera [27], which will be referred to as the camera plugin, was used instead of Cordova's standard camera plugin. This plugin can access the camera's live video stream without the need to open the default camera application on the mobile device. The application was transferred and used with an iPhone SE.

To use the application the user places one finger, preferably the index finger, on the back-facing camera with light but firm pressure to cover the camera. The flashlight on the mobile device is then used to illuminate the finger to further increase the ability of detecting changes within the blood vessels of the finger. The user also tries to cover up the mobile device's flashlight as much as possible but depending on the flashlight's placement in relation to the camera and size of the user's fingers, this is sometimes not achievable.

The camera plugin takes 30 frames per second and draws each frame, one at the time, on a HTML5 canvas object with the size of 150x150 pixels. During testing we noticed that a larger size on the image meant that older devices could not compute the data in time before a new frame was taken, resulting in data loss. The selected size was identified as a suitable compromise of enough pixels to detect changes between frames while keeping the computation time low enough for older devices to still be usable.

From the canvas object we extract every pixel's red, green and blue value, the frame's RGB characteristics, and used it to determine a single value, combined from each RGB channel, for every drawn frame. For that the following equation was used:

$$Y(f) = \frac{1}{n}\sum_{i \in f}[0.299f_i^{(r)} + 0.587f_i^{(g)} + 0.114f_i^{(b)}] \quad (1)\ [28]$$

In eq. 1, *Y(f)* corresponds to the computed average of each RGB value from one frame f where f originates from a sequence of frames between $\{f_1, \dots, f_m\}$. i is iterated through the pixels of f and $\_^{(g)}$ is the indicator of what channel from the RGB is being used, either red, green or blue. The coefficients used for each channel is collected from the ITU-R BT.601 standard [28]. A result of eq. 1 can be seen in figure 2. This method showed promising results over the course of multiple runs of the application, as it computed clear PPG signals reliably. It was therefore selected as the method to base further work on.

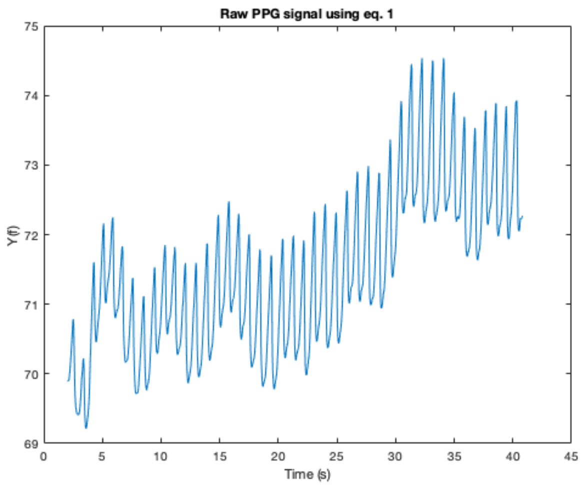

Figure 2: The figure shows a PPG signal collected from our application using eq. 1 on a male user in a state of rest. The y-axis shows the changes of Y(f) in relation to the time in seconds, the x-axis.

During the development of the application, several approaches for calculations of *Y(f)* was implemented and tested to find the most suitable computation. During the first iteration we used a similar computation technique to eq. 1 but without multiplying each RGB channel with a specific coefficient. This made for a simpler calculation, but it showed flaws with what seemed to be randomly occurring spikes, both upward and downward, during the computation of the data. The equation used during this iteration was the following:

$$Y(f) = \frac{1}{n}\sum_{i \in f}[f_i^{(r)} + f_i^{(g)} + f_i^{(b)}] \quad (2)$$

Figure 3 shows a result of when eq. 2 was used to compute the PPG signal.

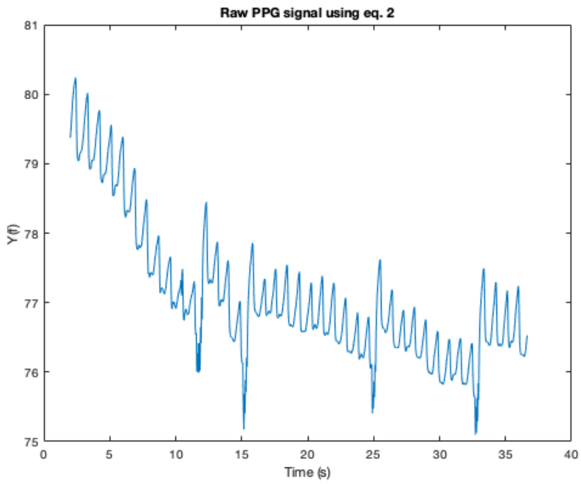

Figure 3: The figure shows a signal collected with eq. 2 and shows how peaks and dips occurred during the computation.

A new method was therefore needed to get a better and more reliable result from the calculations, so the next step we tried was to convert the RGB values into HSL values, which stands for hue, saturation, and lightness, and is an alternative representation of the RGB colour model. Since we are looking for the changes in absorption of the light within the finger, our focus is on the lightness value. RGB values are represented by a number between 0 – 255 for each channel while hue, H, is in the scope of $H \in [0°, 360°]$, saturation, S, in $S \in [0, 1]$ and lightness, L, in $L \in [0, 1]$. To convert the RGB values to HSL, different equations are needed but since we only need the lightness value, and that equation is not dependant on (which is not affected by H or S in HSL - as can be seen see eq. 5 we only needed one equation. Therefor there was no need to compute the conversion from RGB to H or S. To be able to use RGB value in the following equation they first needed to be divided by 255 so that $R, G, B \in [0, 1]$ [30].

$$X_{max} = \max{(R, G, B)} \tag{3}$$

$$X_{min} = \min{(R, G, B)} \tag{4}$$

$$L = \frac{X_{max} + X_{min}}{2} \tag{5}$$

[30]

The average lightness value of a frame is computed by adding up the lightness value of each pixel inside the frame and then the sum was divided with the total number of pixels. Figure 4 shows a signal that has been computed with eq. 5.

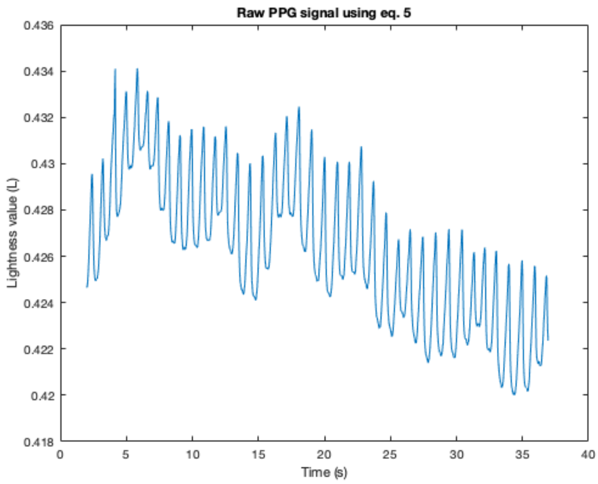

Figure 4: Figure shows a whole signal that has been computed with eq. 5. The y-axis shows the lightness values, and the x-axis shows the time in seconds.

In figure 4 the signal shows clear peaks throughout its whole length, which is promising for our cause especially as the pattern continued when more signals were used. The difference in lightness between a peak and its upcoming valley were small, around 0.05, which can be expected from this method since the lightness values are between 0 and 1, and the frames have low variance between them. While promising, we deemed that this method brought an uncertainty whilst moving forwards with the filtering stage. More so for the eventual use of a peak-to-peak detection method to calculate the heart rate as such a method needs thresholds to be computed. With such a low difference setting up said thresholds this could be an issue and therefore we choose eq. 3 to proceed with instead of eq. 5. We do believe however that it would be possible to use these values computed by eq. 5 and it would have been the preferred method if eq. 3 did not show promising results.

5.2 Pre-processing

During the pre-processing stage, the processed signal computed in section 5.1 is made stationary and filtered. Both these steps were done in MATLAB to easily visualize the results and simplify the creation of filters. For the filters, MATLAB's *filterDesigner* was used in the creation of the filter as well as for generating coefficients needed when applying the filter.

5.2.1 From non-stationary data to stationary data

That data is non-stationary means that it has no mean or variation changes over a period of time or any periodic fluctuations. In figure 2 one can see a clear upward trend over the course of the signal. The upward trend, top part of figure 5 is an indication that the signal is non-stationary. The transition from non-stationary to stationary is done by differentiating the data with one order.

$$Z' = Z_i - Z_{i-1} \tag{6}$$

Z' is the result of the differentiation and Z is the value from the y-axis of the non-stationary data set. The non-stationary data can be differentiated more than once but in this case one time was sufficient to remove the noted trend as can be seen in figure 5. By doing this computation, the first sample will be lost from the non-stationary data which turned out to be an important feature for us. This is because the first values of our signals often held distortions from the turning on of the flashlight, as well as adjustment of the finger. The small loss of samples from the differentiation was therefore not an issue, as it even plays a beneficial role from a practical perspective [31].

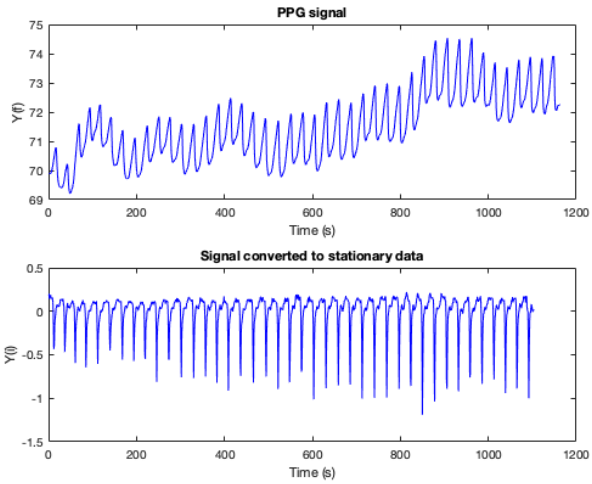

Figure 5: The figure shows how the PPG signal has been detrended and converted to stationary data.

The graph showing the stationary data do appear inverted but produces no issue since the peaks occur on the same value only in a negative manor.

5.2.2 Filter

The raw data is filtered using a 10th order Butterworth IIR-bandpass filter, to remove unwanted high and low frequencies. The Butterworth filter is designed to have a frequency response as flat as possible in the bandpass, meaning that the ripple in the target frequency will be kept at a minimum [32].

The choice of using an IIR-filter over an FIR-filter was to keep the number of coefficients to a minimum. FIR-filters are known to need a higher number of coefficients than an IIR to produce a similar effect. A high number of coefficients for a filter would have a negative impact on the processing time and could require a stronger processor. The processing time also influences power consumption, so lowering the processing time means that we are also able to lower the power consumption of the smartphone. This motivates why we process our data through an IIR-filter rather than a FIR-filter, which otherwise could be an option for its linear phase delay if processing time and energy efficiency are not of concern [33].

The heart rate range we are examine is between 54-180 BPM. The lower threshold was chosen based on the average resting heart rate for adults being between 60-100 BPM [34]. The upper threshold was chosen as 180 BPM as the QCST is designed as a sub-maximum capacity test [4]. A higher BPM than 180 is therefore unlikely to happen during an appropriately executed QCST.

To remove frequencies below and above our heart rate range (54-180 BPM), we used eq. 7:

$$f(x) = \frac{x}{60} \tag{7}$$

Where x is the BPM and *f(x)* are the frequency. By taking the BPM of 54 and 180 and dividing with 60s we can compute the frequency band of 0.9-3.0Hz, which means that the bandpass filter will filter away frequencies below 0.9Hz and above 3.0Hz.

5.3 Calculation of the heart rate

In this phase the filtered signal is used to calculate the heart rate of the user. MATLAB was used to compute the algorithms and generate the visualizations presented in this section.

At this point, the collected signal has been changed from non-stationary to stationary as well as filtered. This allows us to apply a moving window algorithm and perform an autocorrelation of the signal to estimate the BPM.

The algorithm begins with the setup of a moving window which will be used in the autocorrelation function. The moving window size is defined by a number of time lags, which represent the samples we set in the window size. The window is set over a time which indicates a certain dimension of the number of lags. The size we decided to use is five seconds which corresponds to 150 lags of the signal. The window moves itself every 30 lags, which corresponds to one second, over the duration of the signal, thus producing a new heart rate estimation every second. The first window of the signal starts five seconds into the signal from when it began. This is done to eliminate any wrong readings at the start produced by adjustment of the finger. A new BPM value can be computed and provided every second after the first five seconds has passed.

After defining the window size, we used an autocorrelation function that performs a correlation of the signal in the provided window and the result is shown in figure 6. A correlation means that it creates a delayed copy of itself to find repeating patterns. It shows positive maxima at multiples of the period which indicate the period of the heartbeat [35].

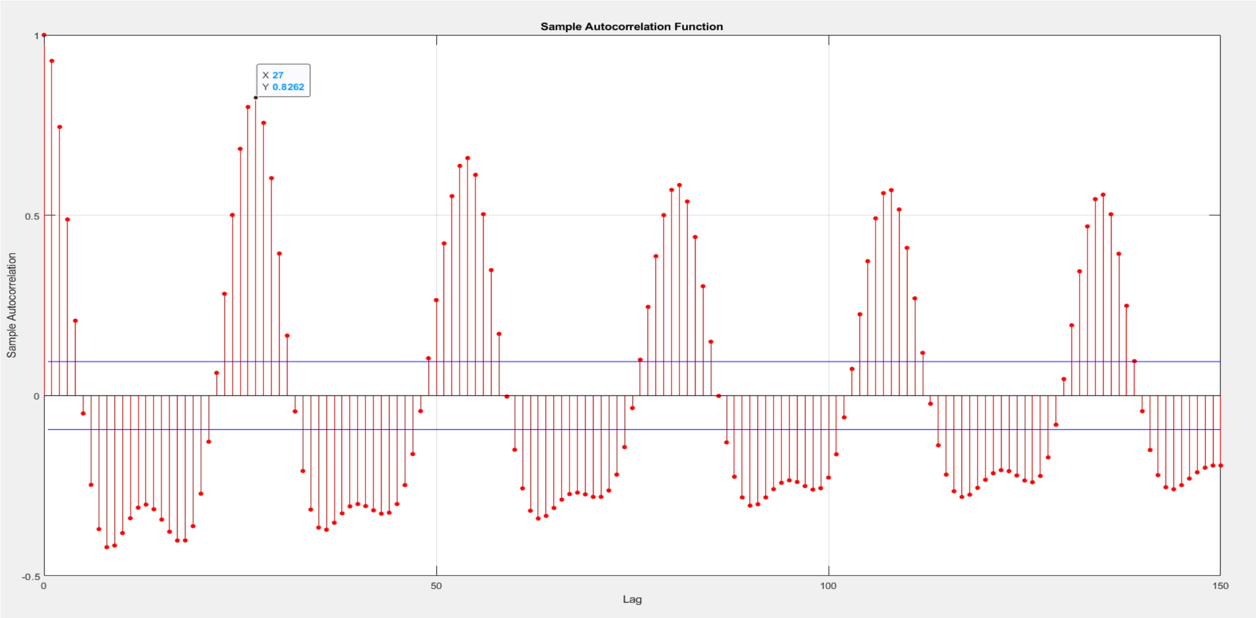

Figure 6: The figure shows the autocorrelation from the first window in one of our signals. The y-axis shows the result of the autocorrelation function, and the x-axis shows the number of time lags.

In order to find the maximum that corresponds to a period between 54 and 180 BPM we limited the search of the maximum between a minimum index (N_{min}) and maximum index (N_{max}). These indexes are calculated from the eq. 8 and determines our range of search for the heart rate. f_s is the rate which the signal is sampled with and *HBR* is the heartbeat rate per minute.

$$HBR = \frac{60f_s}{N} \qquad (8)\ [21]$$

The calculation of N_{min} and N_{max} using eq. 8 produced the following results:

$$N_{min} = \frac{60f_s}{180} = 10$$

And

$$N_{max} \frac{60f_s}{54} \approx 33.33$$

For it to be used correctly both indexes must be an integer, therefore N_{max} will be rounded up to a 34 since 33 will be outside of our range. Doing this changes the minimum allowed BPM to 53 but this will not produce an issue moving forward. We then search for the highest value between N_{min} and N_{max} to locate a peak. If a peak is found, the location of the peak, the time lag (N) of its occurrence, is extracted and used in eq. 8 to calculate the BPM for that window. If no peak was found in the range between N_{max} and N_{min}, the heart rate is beyond our range of search or the data is too noisy.

To demonstrate and evaluate the presented approach the tests previously mentioned in section 4.5 was conducted and the average error, minimum and maximum error as well as the standard deviation in comparison to the ground truth for each signal was calculated. The results are shown in table 1 and table 2.

Table 1: Shows the result in precent when autocorrelation and eq. 8 is used for calculating BPM. The lettering of the signals corresponds to the test it was generated from. Signal A has been generated from test A in section 4.5, signal B from test B and Signal C from test C. The results are rounded to nearest integer.

In precent [%]	**Signal A**	**Signal B**	**Signal C**
Average error	4	2	3
Minimum error	0	0	0
Maximum error	11	5	11
Standard deviation	3	2	3

Table 2: Shows the result in BPM when autocorrelation and eq. 8 is used for calculating BPM. The lettering of the signals corresponds to the test it was generated from. Signal A has been generated from test A in section 4.5, signal B from test B and Signal C from test C. The results are rounded to nearest integer.

In BPM	**Signal A**	**Signal B**	**Signal C**
Average error	3	1	2
Minimum error	0	0	0
Maximum error	9	4	8
Standard deviation	2	1	2

During our iterative process we decided to test a method that did not rely on the autocorrelation function to locate peaks and developed a peak-to-peak algorithm. It used the time in milliseconds between two consecutive peaks, the RR-interval [36], for its estimation of BPM. The algorithm used the same moving window concept presented earlier and began by determining the highest and lowest value in the current window. Those values were then used to define an upper and lower threshold. The thresholds, T, were used to prevent readings of false positives and peaks created by noise. New thresholds were computed in the beginning of each window.

$$T_{min} = Window_{max} \cdot 0{,}4 + Window_{min} \cdot 0{,}6 \tag{9}$$

$$T_{max} = Window_{max} \cdot 0{,}8 + Window_{min} \cdot 0{,}4 \tag{10}$$

The following pseudocode shows how the algorithm located peaks, computed the difference in time between them and calculated the BPM. Until the first peak was found the algorithm handled the fourth if-statement as true. The equation used for the BPM estimation was eq. 11 where $m - n$ is the time difference between two consecutive peaks.

$$BPM = \frac{60000}{m - n} \tag{11}$$

```
For the length of the window
    If the current value is higher than the previous value
        If the current value is higher than the next value
            If the current value is above T_max
                If a previous value has been under T_min since a peak was found
                    Peak is found
                    If it is the first found peak
                        Get the first timestamp
                    Else
                        Get second timestamp
                        Compute time difference between the timestamps
                        Estimate BPM
                        Second timestamp equals the first timestamp
```

Our constructed algorithm for detection and estimation, showed itself to be unreliable and inaccurate. The thresholds that were used were not robust and adaptive enough to handle a more poorly collected signal and false positives was detected or real peaks was not found. Using the RR-interval to estimate BPM has been used in other use cases, for example in the pan-Tompkins algorithm [36], and it is considered a viable solution. However, the algorithm we developed was not sturdy enough for our needs and was therefore deemed invalid and was discarded.

For each of the three approaches presented we also tested how the size of the window affected the estimations and which size yielded the best results. The lowest reachable BPM is 54, ranges from 54-180. This means that the longest period of time possible between two consecutive heartbeats is 1.9 seconds. We therefore decided to set our lowest window size to two seconds. A window size beyond five seconds would produce a risk of missing quick heart rate variations because the heart rate is averaged over the whole window. Additionally, more samples in the window would also requires more CPU and RAM to be used during the analysis. A window size of two, three, four and five seconds, which correspond to 60, 90, 120 and 150 samples or lags, were therefore tested and compared. Each approach presented in this section was tested with the four different sizes and an average error and standard deviation was calculated from each test.

During our testing stage, hints towards a likely delay between the timestamps from our BPM estimations and the estimations from the ground truth was observed. Each estimated value from our different approaches was compared with the correspondent value with the same timestamp from the ground truth. When doing so we noticed that the BPM estimation did not correspond to the ground truth when matched second by second. However, a comparison with nearby values showed a higher accuracy. Our hypothesis was that the algorithm used by the ground truth device introduced a delay. In our data collection stage, we provide a timestamp before the calculations and that could be what created the potential delay. To test our hypothesis, we compared the estimations again but this time with an offset between the PPG data and the ground truth data ranging from -10s to +10s. For each comparison we calculated the average error and standard deviation with different sizes on the window, 2s to 5s, so we could find the most likely delay.

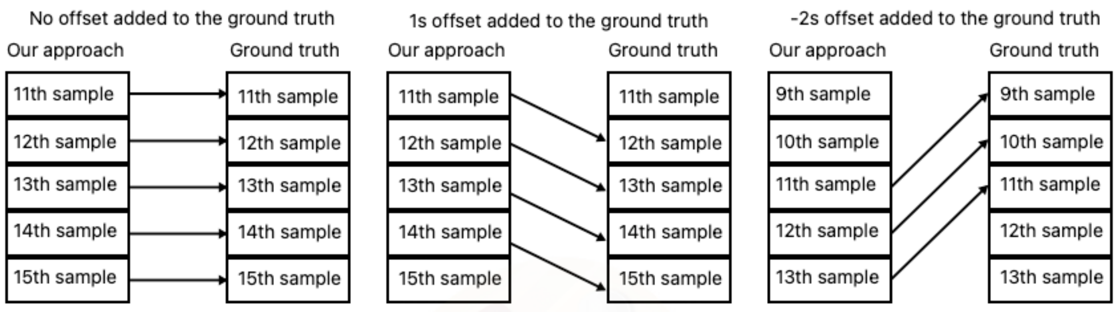

Figure 7: A simple illustration of how the comparison was made. The left figure shows when no offset was added, and the comparison occurred between two samples with the same timestamp. The middle figure shows how the comparison was computed when an offset of one second was added. The right figure shows when an offset of negative two seconds has been added. The comparison starts on the 11th sample so that it can be compared to a -10s offset. To be able to add a positive 10s offset the last sample is tenth last sample of the signal.

The experiment was conducted on the three signals used in the evaluation stage, signal A, B and C. The results indicated that there was likely a one second delay on each of the three signals and our computation was adjusted accordingly. The previously presented accuracies had the adjustment implemented when they were evaluated. When evaluating the offset, we also tested what window size was the most optimal to use. The conclusion was that a larger window size provides a better accuracy for each of the three BPM estimation approaches, regardless of other flaws.

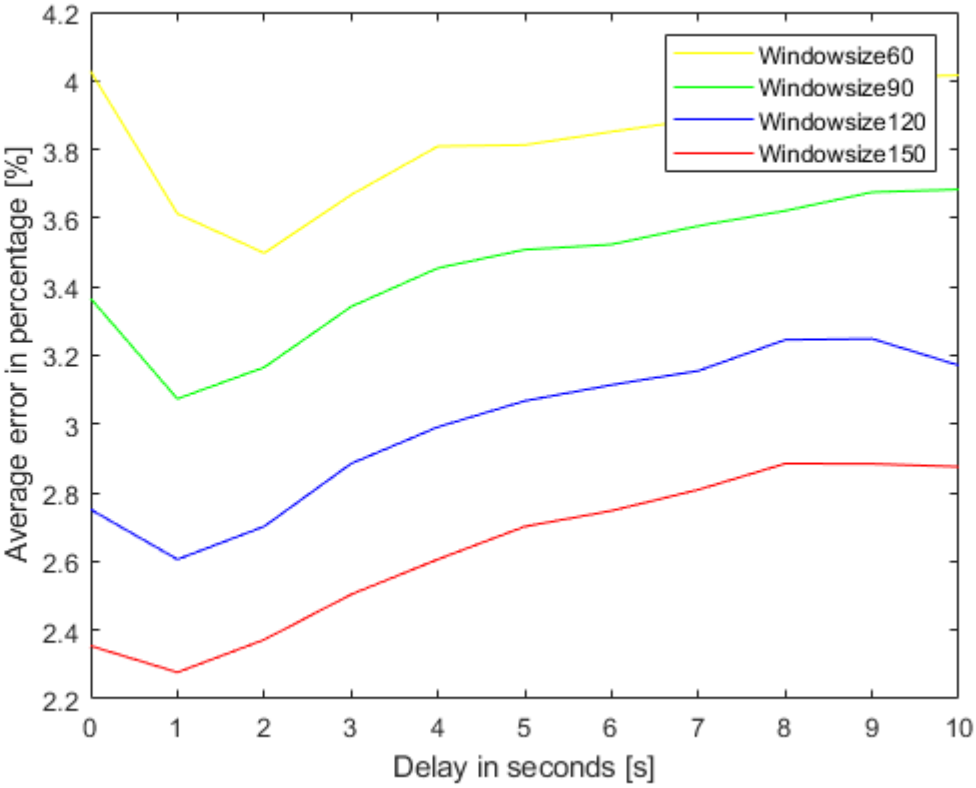

Figure 8: The figure shows the average error in percentage when signal C was used and compared to its counterpart from the ground truth. It can clearly be seen that when an offset of one second is added the average error is the lowest. The figure also shows the effect of different window sizes. The lowest average error is found when the size of the window is at its largest and a one second offset is added.

5.4 Estimating Heart Rate During the QCST

Two participants, one male and one female between the age of 20 and 25, performed three sets each of the QCST with an added minute of rest before each test and one minute after. Estimations of the heart rate was computed for the duration of each test and compared with the ground truth.

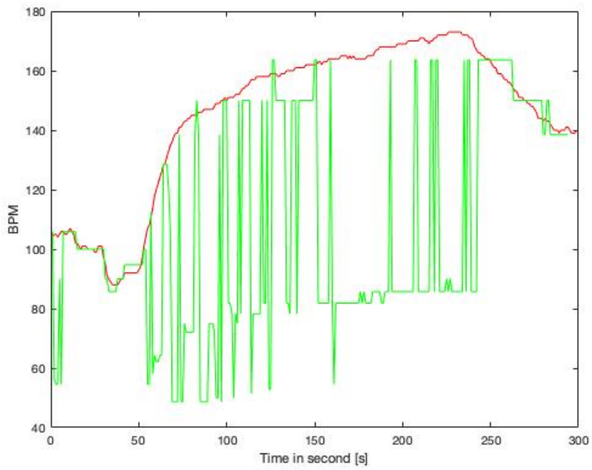

Figure 9: The figure shows the estimation of heart rate from the ground truth, red, and our solution, green, from when a male performed one set of the QCST with the added minute before and after. The actual QCST begins at second 55 and ends at second 250.

For the first minute of the test, second 0 to 55, the user was at rest and both lines correspond with each other well. When the actual QCST began, after second 55, the lines do not match until the user again is in a state of rest, after 250s in figure 10. The noise produced during the QCST is most likely caused by the movement of the whole body which in turn leads to displacements and moving of the finger on the camera. Each of the six sets of tests showed the same trend as figure 10. Implementation of a post-processing stage would be needed if one wishes to be able to estimate the heart rate while performing the QCST. The current version cannot coup with the generated noise. In reality however, the BPM estimation only needs to occur after the QCST has finished and therefore it is of interest to only analyze the last minute of each test and not the full length. Table 3 shows the average result from the six tests.

Table 3: Shows the combined average error, minimum and maximum error as well as the standard deviation from the six QCST performed by the two participants. The column shows the result of when the last minute was calculated. The results are rounded to nearest integer.

	Average of the last minute
Average error	15 %
Minimum error	0
Maximum error	115

Standard deviation	10 %

The results presented in table 3 shows that the average error and the maximum error in the last minute of the QCST is high. However, when each test was analyzed separate, we noticed that in three of the tests the signal was heavily distorted and, in some areas, unreadable which led to fault readings.

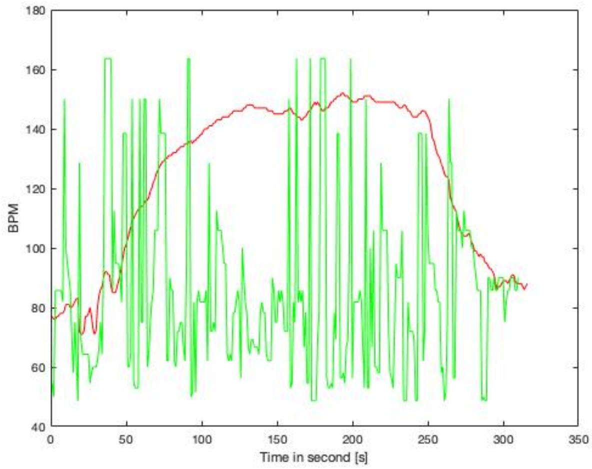

Figure 10: The figure shows when estimations of heart rate was done on a heavily distorted signal. The green signal is the estimated values and the red signal represent the ground truth.

If the distorted signals are discarded when evaluating it shows a different result as can be seen in table 4.

Table 4: The table shows the combined average error, minimum and maximum error as well as the standard deviation of the last minute without the three distorted tests. The results are rounded to nearest integer.

	Average of the last minute without the distorted tests
Average error	6 %
Minimum error	0
Maximum error	52
Standard deviation	10 %

The average error have been reduced significantly compared to the results shown in table 3. They are however still higher than the result from table 1 and shows a high maximum error. When the three minutes of QCST was completed the participant entered a state of rest and did so in a seated position. Our hypothesis is that noise was generated in the beginning of the rest as a result of going from a standing position to a seated position. During that small window the finger could have been moved on the camera and high errors could be generated despite being in a state of rest. Hints towards this can be seen in figure 10 as a much higher spike occurred right after the 250 mark and after that the two signals matched each other.

6 Discussion

In this section we discuss and reflect on different parts of our thesis and a comparison of our work with the related work is presented.

6.1 Threats of validity

The access to how the application gathers data from the ground truth and estimates the BPM is strictly limited and not reachable for its user. There is therefore no way for us to affect or analyze the process and e.g., averaging of the BPM might occur without our knowledge which might impact our results. Our presented solution has only been tested on users with a light skin tone and no modification has been done to handle darker skin tones which might be required to reach the same level of accuracy.

Older mobile devices then the one used, iPhone SE, has not been tested and could pose a threat as the presented solution might not work as well on mobile devices with lesser RAM and CPU then what is being currently used. It is possible that older devices cannot achieve the same result presented as it might not be able to handle the computations in time. The resolution of the camera might also be too low to detect vital changes in the blood vessels.

6.2 Testing stage

The work presented in this thesis has been going through an iterative testing stage and each new implementation was followed by an intensive testing phase. However, due to restriction in regard to Covid-19 a very strict limitation on the number of participants needed to be enforced. This crippled the amount of QCST test cases that was generated, and the result was needed to be evaluated with less data than optimal. A larger and more diverse group of participants with different age, gender and skin tone would give a more trustworthy result. We do believe that gender would not interfere with our current result since one’s gender do not affect the part of the body we are gathering data from. Age could show a small negative impact on our result as one’s skin can become rough and hardened over the years which could make it harder to detect changes with the mobile camera. As mentioned above one’s skin tone could produce a large negative impact on the result. A darker skin tone absorbs more light than a lighter tone and volume changes in the blood vessels could therefore be harder to detect which can result in false readings.

Despite the circumstances a large amount of data was collected, both during the development and for demonstration of the final solution, from the two participants. The generated data is deemed valid to base a result upon, but more test cases would be needed to increase its validity.

6.3 Comparison towards other studies

In the related work article [21] authors used the same concept of a smartphone camera and tried to extract BPM from users seated in a state of rest using PPG and a sample rate of 250Hz. Their proposed solution had a measured accuracy of 100%, both with clean and noisy signals, when compared with the BIOPAC system. Our thesis has shown that it is possible to use the same concept in a more active state and with a much lower sample frequency with the trade-off of having a lower accuracy, above 90% after physical activities has been performed. This goes to show that while using a smartphone camera it becomes more unreliable to base heart rate estimations if moving.

In the paper [22] authors evaluated an application called FibriCheck, by asking patient that was recovering from cardiac surgery to register their heart rhythm. Their method of approach was to register the rhythm from a smartphone camera that uses the PPG, and then upload the PPG signal to a server that calculated and analysed the rhythm.

The similarities from this paper and our thesis are based on the usage of a smartphone camera to take pictures and the PPG. In their paper they use the camera and the PPG to register heart rhythm, while they offer a comfortable way by doing so. In our thesis we use a similar method but during other circumstances as we based our thesis on calculating the BPM with the usage of a camera and PPG during the QCST and not the heart rhythm as described in the paper.

In the paper [23] authors used a smartphone to extract the heart rate from images. They divided up each frame into RGB colouring channels to spot any differences in colour within the frame which then would be calculated to determine the BPM with the use of autocorrelation. Their solutions had a highest average error of 7,33% with the ICA and 4,39% without it.

Their study and our thesis have many similarities as much of our work has been based upon their approach. In the subject of the frame rate being set to approximately 30 fps, the method of taking the frames and divide them into the RGB colour channels and then normalizing the signal. The differences are the amount of noise we are getting from our signal. Because of the circumstances of the QCST we are producing much more noise than them and because of that we implemented a filter for our signal before calculating the BPM. In a state of rest our approach reached a maximum average error of 4 % and when a QCST has been performed 6 %, when excluding the distorted tests.

7 Conclusion and Future work

In this chapter we summarise and present our solution concerning each of our research questions and what can be done to improve our work on the matter.

7.1 Conclusion

In this thesis the goal was to develop an algorithm that calculates the BPM during the QCST. This contributes to research by addressing how an algorithm can compute and calculate a heart rate. We do this by addressing these research questions:

- RQ1: How can heart rate be computed by a mobile phone during a step test?
- RQ2: How can the heart rate accuracy of the algorithm be determined?

Presented in the earlier part of chapters 5 the camera on a smartphone was used to collect a PPG signal from low-resolution images, so that the heart rate could be computed. As presented in the later part of chapter 5, our calculation of the heart rate is both well tested and accurate at rest in comparison to the pulse band, our ground truth, and in conclusion the RQ1 is therefore answered.

By comparing our measured values with a ground truth and utilizing different test scenarios and test cases we could determine the accuracy of the heart rate algorithm. The accuracy is calculated as average error in precent and therefore a low value indicates a high accuracy. The results presented in chapter 5 answers RQ2.

7.2 Contributions

The initiative of this thesis was to develop a heart rate estimation algorithm that could be used when performing the QCST using only a mobile device. This thesis has presented a working solution which takes advantage of the mobile camera and PPG for its estimations. The proposed solution can be used in its current state or as groundwork for future development in regard to a mobile-based QCST and other physical performance tests.

7.3 Future work

Future work will be to convert the parts conducted in MATLAB, pre-processing and heart rate estimation, to JavaScript so it can be implemented into Mobistudy's application. Furthermore, optimizations to the algorithm could be done e.g., by further research if IIR or FIR is the most optimal filter to use in this circumstance as it has not been tested enough to exclude the FIR filter in this thesis. The filter coefficients could also be improved by finding the lowest possible number of orders that can be used without producing a negative effect in performance. For testing and comparison of the algorithms more signals when higher cardiovascular activities occur will be collected to further evaluate the performance of the algorithms during rapid decrease of heart rate.

In regard to the QCST further development include e.g., a step-detection algorithm and a metronome. This is so the user only needs a mobile device to perform the test and to ensure that the user actually performs the test by tracking the steps.

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